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Link Adaptation Strategy for Underwater Acoustic Sensor Networks: A Machine Learning Approach

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Abstract: Due to growing concerns regarding their use in fields including oceanography, commercial marine operations, and military surveillance, demand in the exploration of underwater sensor networks for marine studies has developed. Network channels for underwater sensor network (USN) rapidly change (spatially and temporally) depending on the surroundings. To increase system efficiency by adjusting transmission parameters to channel fluctuations, it is alluring to utilize adaptive modulation and coding (AMC) for USNs. In order to determine the best link adaptation method based on the channel quality, this article focuses on evaluating a measured sea trial dataset utilizing a rule-based approach (i.e., three-dimensional evaluation, modulation-wise analysis, and a fixed-SNR strategy). To determine the optimum AMC combinations in terms of channel adaptively, we draw a situation of the measured USN data rate versus Bit Error Rate (BER) and Signal to Noise Ratio (SNR). The work further extends to apply machine learning (ML) methods to identify the MCS levels by looking into the channel characteristics due to the non-reversibility limitation of the rule-based strategy. One of the ML methods we used for the investigation, gradient boosted regression tree (GBRT), exhibits impressive accuracy of 99.988% in classifying MCS levels. The MCS levels are related to channel statistics and signal characteristics, particularly those that are susceptible to SNR and BER limitations, using an ensemble of trees that learns from the buoy and base station's uplink data.

Keywords: Underwater sensor network, machine learning, link adaptation, gradient boosted regression tree.

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1. Introduction

Networks of underwater sensors have a lot of possibilities for studying and analyzing the

aquatic environment. Underwater sensor network (USN) are therefore widely accepted as the sole strategy practical for long-distance underwater connections, and they have been widely used in a variety of contexts. Many scientific, military, and civilian applications, such as submarine communications, underwater security surveillance, research data collection at ocean bottom stations, autonomous underwater vehicle offshore oil exploration, and data transfer in underwater sensor networks for environmental monitoring, all require high quality of service [1]. The underwater acoustic channel has difficult qualities, like a long delay and a wide Doppler spread, which cause frequency and time-selective fading, and it is crucial to cope with these. Moreover, the performance of the UAC network is significantly impacted by fading, Doppler dispersion, and multipath propagation. In contrast to conventional wireless channels, the data loss in a USN relies both on frequency of a signal [2]-[5] and the distance between the transmitter and receiver. The signal frequency causes absorption loss as a result of the conversion of acoustic energy to heat. Therefore, as compared to the normal terrestrial channel model, the underwater channel faces a number of difficult challenges.

Reusing of Frequency and cellular principles are more attractive in order to improve the capacity and coverage for a USN due to the severe restrictions on the bandwidth utilization in a USN [6]-[8]. This study focuses on the cellular form of USN architecture, within which the 1st tier is only seen as an area that causes interference and the core cell is the area of concern. In fact, the SNR versus block error rate (BLER) has been used to analyses the link-level simulation (LLS) [9]. We use the BLER curves obtained by the LLS under white Gaussian noise (AWGN) with regard to appropriate modulation and coding scheme (MCS) values in order to produce the BLER in the SLS without performing the actual computations. The BLER under a fading channel can be predicted using an AWGN-equivalent signal-to-interference-plus-noise ratio (SINR) [10]-[13].

Reuse of frequency and cellular principles are more tempting to improve the capacity and coverage of a USN due to the severe bandwidth restrictions in a USN [14]-[16]. A 12-path Rician fading channel has been employed in a simulation-based link adaptation (LA) technique [17] for strategic LA. This method considers only a few parameters, namely modulation level with a constant coding rate and repetition patterns, for a highly variable UAC network channel. Additionally, the priority rules which were developed to separate the possible modulation levels from those that overlap—are predicated on a number of presumptions. This limits the approach's usefulness from a practical standpoint. A model of channel for the UAC network is also very difficult to develop, in contrast to scenarios for terrestrial networks, such as the knife-edge diffraction prototype, the Longley-Rice model, the Okumura design, etc.

It is challenging to spot modulation within actual communication due to the instability and complexity of underwater audio communication systems. Time-domain turbo equalization, sparse adaptive convolution cores, and frequency-domain turbo equalization are some novel techniques for underwater audio communication, however they still struggle with high computational cost and poor classification success rates. Deep Learning has been used to achieve classification accuracy of over 99% [18].

In this research, we use machine learning (ML) to categorize the MCS levels by addressing the aforementioned issues. We concentrate on the examination of datasets from a USN network with transmitter and receiver distances of approximately 3 km, 2 km, and 1 km (stored on a single drive: link [19]). The datasets included a variety of measured channel properties as well. The goal of this study is to create a link-adapted mechanism that can increase spectral efficiency in respect to any channel circumstances while preserving the appropriate level of secrecy and dependability. We compare the throughputs for the given two distances for various rule-based techniques, such as 3-D analysis, modulation-wise assessment, fixed-SNR strategy, etc., with the combined effects of SNR and BER. Then, using a variety of trustworthy ML methods, including the better-performing gradient boosted regression tree (GBRT), we categorize the modulation type on our datasets while

adhering to SNR and BER limitations, then evaluate the accuracy.

Despite our best efforts, the rule-based analysis reveals that none of the solutions produce a strong result because of the non-reversibility problem. Our monitored sea trial files demonstrate the enormous amount of fluctuations the channel experiences throughout the day and night, summer and winter. In addition, there are additional variables that must be taken into account and monitored during the sea trials. These variables include pilot spacing (PS), coherence bandwidth (BW_{coh}), BER and maximum estimated delay (MED). The rule-based LA approach was defeated by the statistical ML algorithm-based analysis.

We discuss the related work in Section II. Then, we presents the USN architecture in Section III. The rule-based strategy, including the three-dimensional analysis, fixed-SNR strategy, and modulation-wise analysis are described in Section IV. Details regarding ML in the USN are provided in Section V. Results of the MCS classification using ML are presented in Section VI. In Section VII, we conclude this paper.

2. Related Works

Finding USN features has been the subject of a lot of research in the literature. This section briefly reviews the wide spectrum of related contributions. USN researchers have recently given these areas a lot of attention, including disaster prevention, guided navigation, surveillance, environmental and pollution monitoring, and commercial and scientific applications [20]. It is required to facilitate communications amongst underwater devices for the viability of these applications [21]. Several features of USNs, including physical layer difficulties, transmission modalities, and protocols in the network, link, and transport layers, are still without standards [22]. The author describes resource modelling in a virtual ocean setting in [23]. For underwater networks, a delay-aware scheduling technique is put out in [24], [25] contrasts the standard underwater network design with the suggested orthogonal signal division technique.

We go over the popular strategies for the PHY and MAC layers in this part, including carrier-sense multiple-access (CSMA), frequency division multiple-access (FDMA), code division multiple-access (CDMA), and time division multiple-access (TDMA). The FDMA solution may not fully resolve the problems of UAC networks due to the restrictions on the bandwidth utilization in USN channels and demanding characteristics like long latency and strong Doppler spread [26]. However, a large portion of the research used the FDMA strategy for unique topologies and node placement constraints in UAC networks. The OFDM-based MAC protocol for USNs is described by the author in [27]. The proposed MAC design in [28] takes advantage of a deteriorating acoustic channel's multi-path properties. Before accessing the carrier during the contention process, the nodes in the CSMA technique detect its availability in the channel.

Due to the lengthy acoustic signal transmission delay, carrier sensing is unable to identify the channel's actual condition. There could be serious collisions as a result. Multiple access collision avoidance protocols, in which nodes lock the channel with earlier request-to-send and clear-to-send messages, were developed to address this problem. However, this reduces throughput [29]. The author of [30] investigates the adaptability of the multiple access collision prevention strategy for multi-hop UAC networks. The concealed terminal problem is alleviated by the collision avoidance method suggested in [31], which is helpful for UAC networks. Numerous studies have shown that the near-far dilemma in CDMA can be resolved by regulating the transmission power. A hierarchical tree topology that multiplexes nodes within the same hierarchy level using different orthogonal codes was suggested in [32]. To loosen the limits on network topology, the authors of [33] suggested several network sizes and architectures. In [34], the authors contrasted the Tone-Lohi and slotted floor acquiring multiple access MAC protocols in terms of performance (energy usage and throughput).

Numerous TDMA-based protocols have been put out in the literature to address TDMA's drawbacks. The authors of [35] carried out a real-time investigation of UAC networks. The shortest route between the source and sink nodes is chosen by the routing policy. Through simulations, they assessed the effectiveness of the suggested MAC protocol and route model to solve the real-time communications in a USN. A USN network also needs a multi-hop network to cover a wide area. For USN, many network architectures have been put forth in the literature. The depth detected by each node was used as a routing metric in the depth-based routing protocol, which was proposed in [36]. A different dynamic routing algorithm that is based on the number of hops between the transmitter and reception nodes was put forth in [37].

The dependability and energy efficiency of UAC network protocols were studied by the authors in [38]. Based on many characteristics, including routing method scalability, mobility, throughput, network architecture, scheduling, acknowledgment, and contention techniques, they weighed the benefits and drawbacks of various protocols. The efficiency for a three-dimensional USN network with a one-hop portable relay was examined by the authors in [39]. The packet transmission rate was used as a performance metric when analyzing variable USN with movable relays and stationary communications nodes. A survey of routing protocols for USN was presented in [40], where each protocol's routing method, advantages, disadvantages, and delay were discussed. To prevent interference in UAC networks, the authors of [41] developed a mobility-assisted geo-opportunistic routing paradigm. The data is directly collected by the mobile nodes from the void zones, which reduces the amount of data flow on intermediate nodes.

3. Results and discussion

Numerous contributions have been made to the topologies of cellular networks as well as to the topic of frequency reuse in terrestrial wireless networks. Consideration of wireless and frequency reuse in a USN is essential given cellular networks' incredible successes. Given that the USN is still being developed, serious study and attention must be given to this problem. The cellular-based network layout for a USN network is appealing due to bandwidth restrictions. The interface 3 connection is used to link the main underwater base station (MUBS) to the core network. Our primary aim is three underwater base station (UBS), which is connected to MUBS via interface 2 and to the USN via interface 1 as shown in Figure 1. The 100 Hz acoustic wave is utilized as the carrier in Interfaces 1 and 2. 3~8 kHz to 16~20 kHz, 60 ~ 70 kHz connections are allocated to the UBSs, and 22 ~ 27 kHz to 48 ~ 58 kHz frequencies are allocated to the sensors, respectively.

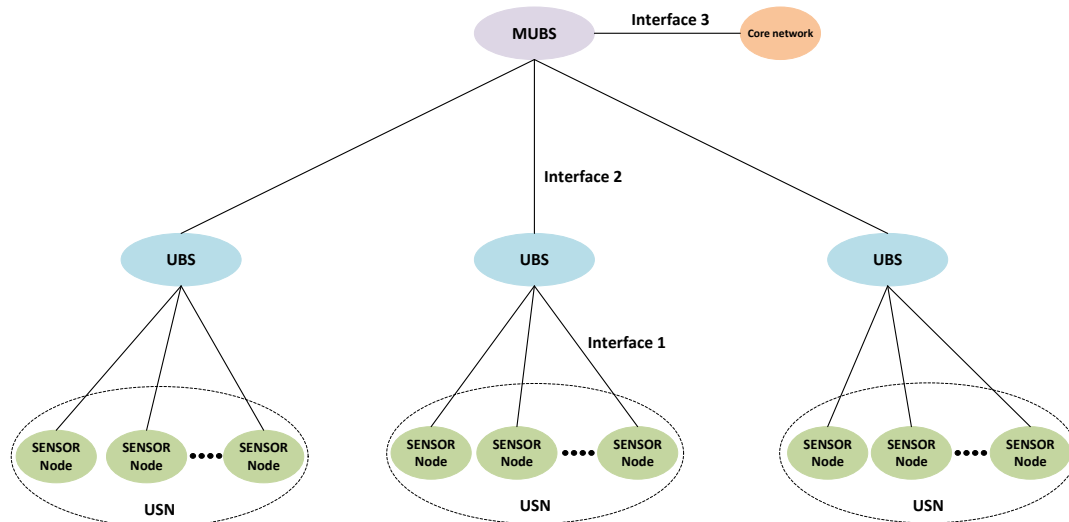


Figure 1: USN Architecture

Two different measurable dataset types are the foundation of the study. The receiver (Rx) and transmitter (Tx) were separated by two distinct distances, namely 3 km and 1 km. The dataset contained 417 groups of experimental results and 288 combinations of various sorts of parameters, which is a strong reason to choose the appropriate MCS levels gradually. Three steps were taken in the dataset analysis process: a three-dimensional analysis, a modulation-wise assessment, and a fixed-SNR technique. The Incheon dataset, in contrast to the dataset, contains 10,105 sets of experimental data and 108 different parameter combinations. It is hard to evaluate this massive dataset using any other method except the ML methodology.

3.1. Dataset Analysis and Preprocessing:

In the three-dimensional analysis, the goal is to investigate three parameters simultaneously since we must examine these parameters in order to obtain a link adaption curve for every modulation. For the 1 km dataset, our initial intent was to base our decisions on SNR, data rate, and BER. We choose BER as the random variable since BER varies with the RMS delay spread. BER might therefore be a reliable parameter for the assessment. Additionally, research for binary phase-shift keying (BPSK) reveals that the majority of MCS levels are in the blue region, indicating low BER for those levels. High BER regions only exist where data rates are higher. In the minimum SNR zone, a less number of MCS levels have larger data rates.

Data for various coding rates for various modulations, such as BSPK (1/3), BPSK (1/2), QPSK (1/2), QSPK (1/3), etc., have been separated. For various PS and RP combinations, MCS levels have been thought to be discarded using BER, coherence bandwidth, or root mean square delay spread. According to our research, reliable predictions are (2, 1), (1, 1), (8, 1), (4, 1), (2, 3), (1, 3), (1, 9) and (4, 3). After combining the MCS levels with consistent repetition patterns, we eliminated those that had overlapping data rates and SNR, leaving us with the 21 finalized MCS levels.

4. ML-based LA Algorithm

If we summarize the outcomes of the rule-based approach, we can say that the SNR is slightly declining for additional data rate, which is the reverse of the LA scheme. The data rate is decreased for high BER. BER is inconsistent but often incremental. When SNR rises at a given modulation level, the data rate falls. Even though it resembles the LA curve for a fixed-SNR method, only a tiny portion of MCS levels follow this LA trend. A fixed-SNR approach is incompatible with the LA method for 3 km. Therefore, compared to a terrestrial wireless network scenario, it is more difficult to create a network model for a USN, such as the knife-edge diffraction model, the Longley-Rice model, the Okumura model, etc. Additionally, there is a time discrepancy between the channel assessment and the use of modified MCS levels.

Delivering the collected data from the receiver to the transmitter for processing and classification at the suitable MCS level is necessary for the real-time implementation of the classification results. However, there is a frame delay of around two seconds between the transmitters and receivers, which makes it difficult to apply the modified MCS values for LA. A receiver strategy based on rules may be the answer to these issues. However, link adaptation from measured data may be possible, but link adaptation from the opposite may not be possible, as is the situation in a recognized wireless channel.

Preparing the dataset and identifying the characteristics with the highest variances are the first steps in the ML technique for our investigation. These characteristics are probably going to factor into the classification choices. A single algorithm cannot resolve all ML issues; instead, selecting

the best ML algorithm requires a process of try and error. The qualities of an algorithm, such as its classification accuracy, speed, training time, amount of data needed to train it, implementation challenges, etc., must be considered while choosing the best method for a given task.

4.1. Gradient Boosted Regression Tree (GBRT):

Binary partitions created by bisecting the input parameters into regression trees are referred to as nodes, while leaf nodes are terminal nodes. The mean of the modulations according to the transmissions is how the regression tree calculates the modulation within each node. The mean square error (MSE) among the anticipated value and the measured value is reduced by this method. The training algorithm chooses the input parameter and its corresponding value to maximally lower the total MSE for a specific training dataset in order to best split the input variable space in each iteration. Until the required MSE for the tree is attained, or until the intended maximum depth is reached, this node-splitting process is repeated recursively. With heterogeneous datasets, such as inputs that are numerical, categorical, and ordinal, regression trees can be used. Additionally, it can transparently handle missing inputs. Trees are among the most adaptable statistical learning techniques now in use because of these two characteristics. GBRT can nonetheless generate low-bias estimates, but the estimates may be vulnerable to high variance, just as other statistical learning techniques.

Researchers have employed ensembles of trees to address the high-variance problem in statistical learning and have produced estimates that are more reliable than single trees. GBRT are subjected to the broad learning algorithm AdaBoost in boosted trees. Numerous trees are trained iteratively using all of the training data, with each iteration adjusting the weights of the training set and predictions based on how accurately the values were predicted. The aggregate boosted tree classifier delivers gradually more precise prediction as a function of the total trees because the final, aggregated prediction from boosted trees is a mixture of weighted projections from each tree.

5. Simulation Results

We divided the datasets into 2 categories, using 30% of the data to assess the classification accuracy of all the techniques and 70% of the data to train the model. For GBRT, 2000 aggregate constituent trees are used, each with a minimal leaf size of 20 and a minimum parent size of 20. We use boosted tree regression analysis to achieve the greatest (and almost perfect) classification accuracy of any ML method for the aforementioned Incheon dataset, which was 99.987%. To determine the correlation between the calculated BER and the received SNR, signal parameters, and other relevant channel metrics that define the signal distortion, we employ GBRT.

We determine the throughput in Fig. 2(a) using (14) for both the suggested and traditional link adaption strategies. Since the receivers are attaining the throughput on the same values, the throughput slopes are not uniform due to the lack of throughput precision points in Fig. 2(a). The suggested link adaptation technique has a throughput of about 1.1 kbps at the 50% CDF, whereas the traditional LA algorithm could only manage a throughput of about 0.86 kbps. This is seen from Fig. 13. As a result, the GBRT technique outperformed the traditional one by about 24.5%. The system is adjusting the connections continuously with less computational complexity, which is the clear reason why the suggested link adaptation technique achieves the greater throughput.

As can be seen from Fig. 2(b), the proposed link adaption strategy reduced the likelihood of outages. For instance, utilizing the suggested link adaption technique, it is simple to see that approximately 68% of receivers are experiencing an outage when comparing the outage probability efficiency at 2 dB threshold of SINR. On the other hand, when the traditional link adaption mechanism is used, 82% of receivers are down. As a result, the suggested link adaptation works effectively in the USN because it has the advantages of reduced computing complexity and

seamless link adaptation.

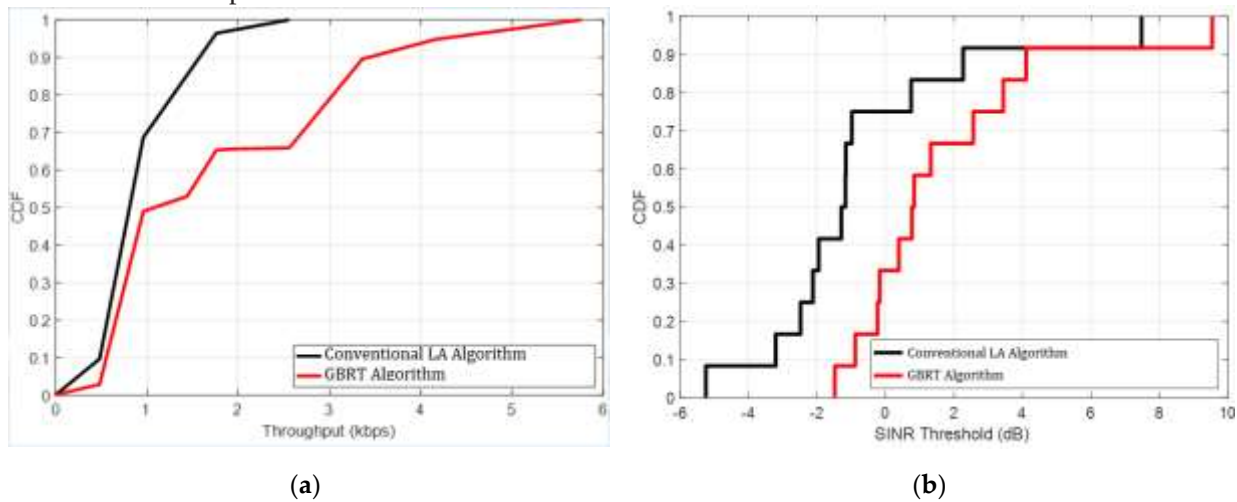


Figure 2: Performance matrix to compare proposed GBRT Vs Conventional LA algorithm: (a) Throughput; (b) SNR Threshold.

6. Conclusion

In this paper, we used analysis to thoroughly examine the USN measured data. With the help of the results, a link-adapted system that can increase efficiency in accordance to any network conditions while maintaining the appropriate level of secrecy and dependability will be created. We looked into a few trustworthy ML algorithms for categorizing MCS levels, and GBRT delivered the best result with a 99.9867% classification accuracy rate. The SNR threshold for the USN must be adjusted on the receiver side to distinguish between each MCS level, similar to 3GPP LTE. In our scenario, we have a number of metrics, including SNR, datarate, BER, coherence BW, etc. The channel's impact on various metrics over a specific time period can be seen using the BER plot.

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